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Air quality change and public perception during the COVID-19 lockdown in India

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ABSTRACT

This study aims at analyzing the change in air quality following the COVID-19 lockdown in India and its perception by the general public. Air quality data for 100 days recorded at 193 stations throughout India were analyzed between 25th March to 17th May 2020. A nationwide online survey was conducted to obtain public perceptions of air quality improvement ($n = 1750$). On average, approximately 40% improvement in the air quality index was observed, contributed by a reduction in 40% of PM_{10} , 44% of $PM_{2.5}$, 51% of NO_2 and 21% of SO_2 . There was a significant difference between the levels of all the pollutants before and after the lockdown ($p < 0.05$), except ozone. The correlation between PM_{10} and $PM_{2.5}$ with ozone was significant after the lockdown period, indicating that a significant portion of the particulates present in the atmosphere after the lockdown period is secondary. The values of $PM_{2.5}/PM_{10}$ were found to be >0.5 in North East states and this observation points to the long-distance transport of $PM_{2.5}$ from other places. The survey for public perception showed that 60% of the respondents perceived improvement in air quality. Household emissions were perceived to be a significant source of pollution after the lockdown. An odds ratio (OR) of 17 (95% CI: 6.42, 47.04) indicated a very high dependence of perception on actual air quality. OR between air quality and health improvement was 5.2 (95% CI: 2.69, 10.01), indicating significant health improvement due to air quality improvement. Google Trends analysis showed that media did not influence shaping the perception. There was a significant improvement in the actual and perceived air quality in India after the COVID-19-induced lockdown. PM_{10} levels had the most decisive influence in shaping public perception.

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1. Introduction

Pollution has become the major environmental reason for many diseases and premature deaths across the globe (Landrigan et al., 2017). The escalated levels of air pollution can be attributed mainly to rapid strides in industrialization and increased vehicular traffic. Other sources of air pollution include burning wood, dry grass, fossil fuels such as coal and construction activities (Gurjar et al., 2016). The Central Pollution Control Board (CPCB) of India identifies 17 different categories of industries in the country (CPCB, 2021). The air pollutants emitted from these industries include ambient particulate matter (PM) of various sizes, metals, gases, and many organic compounds. >200 million vehicles (MORTH, 2019) on roads also contribute significantly to air pollution in India. It is estimated that the emissions from the transport sector account for almost 56% and 70%, respectively, of the total $PM_{2.5}$

and PM_{10} load. Of the total $PM_{2.5}$ contribution from the sector, 70% is from diesel-operated vehicles (Guttikunda et al., 2019). Exposure to air pollutants triggers asthma, wheezing, rhinitis, eczema (Norbäck et al., 2019) and allergic disease (Brandt et al., 2015). Additionally, changes in several neurobehavioral functions in children and depression and cognitive impairment among the elderly have been the after-effects of continuous exposure to polluted air (Costa et al., 2020). Studies have indicated that poor outdoor and indoor air quality increases mortality in some of the major cities in India (Lelieveld et al., 2015; Nagpure et al., 2014). To a large extent, air quality is related to human activities. However, it is impossible to restrict human activities to effect any improvement in air quality, although it is possible to restrict non-essential activities to some extent (Bao and Zhang, 2020). However, there can be instances when even essential activities are restricted as a response to unusual situations.

Lockdowns restricting physical human interactions are non-pharmaceutical interventions to control the spread of contagious diseases (Atalan, 2020). At the end of 2019, Coronavirus disease

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19 (COVID-19) started spreading across the globe. WHO confirmed the transmission of COVID-19 through respiratory droplets among humans (WHO, 2020). The coronavirus outbreak became an international crisis with its spread to many countries, resulting in the deaths of many and interruption of normal life (Gautam et al., 2020). Nationwide lockdowns had to be implemented in most of the affected countries to contain the spread of the disease (Oraby et al., 2021). The first confirmed case of COVID-19 infection in India was reported from the state of Kerala on 30 January 2020 (Andrews et al., 2020). The country observed a jump in coronavirus cases by the 4th of March. On 22 March 2020, a 14-hour voluntary public curfew was imposed in India, followed by lockdowns in some districts as well as major cities where COVID-19 positive cases were identified (Kumar and Krishnaswami, 2020). The Prime Minister of India declared a nationwide lockdown for 21 days with effect from 25th March 2020 as a part of lockdown 1.0 (Ministry of Home Affairs, 2020). This was further extended up to the 3rd of May (lockdown 2.0), with some conditional relaxations in areas where limited cases were reported. From April 20, agricultural businesses, public work programmes, cargo vehicles like trucks, trains and flights were allowed to operate. Banks and other necessary Government departments, small retail shops, etc. started to function following the social-distancing norms (Ray and Subramanian, 2020). Even after these restrictions, the number of COVID-19-positive cases was on the rise, and the third phase of lockdown was implemented up to 17th May (lockdown 3.0). In the third phase of lockdown, the entire country was split into three zones based on the number of cases, viz., red, orange and green zones. Red zones were under complete lockdown and normal movements with 50% occupancy in public transport were allowed in the green zone (Thacker, 2020). In the fourth phase of lockdown between 18th to 31st May (lockdown 4.0), the red zones were further divided into contaminant and buffer zones. In this phase public transport and all the shops except those in malls were allowed to operate. Take-away in restaurants, wedding with 50 guests and funerals with 20 people were allowed (The Hindu Net Desk, 2020). The unlock of restrictions started from June 1, 2020 (Government of India, 2020).

As a result of the series of lockdowns in India, industrial activities, transportation by all modes, and almost all other polluting activities decreased drastically. The country's industrial, commercial and business sectors have felt the negative impact of COVID 19 (ICRA, 2020a, 2020b, 2020c). Perhaps the only area where the shutdown had a positive impact was the air environment. The shutdown resulted in the drastic reduction of some pollutants discharged into the air environment (Nigam et al., 2021; Srivastava et al., 2020). Consequently, there was a significant reduction in pollution levels in most cities of India (Gautam et al., 2021a, 2021b; Gautam et al., 2020; Gautam, 2020a, 2020b; Gautam et al., 2021c; Gupta et al., 2021; Joshi et al., 2020; Karuppasamy et al., 2020). The same trends were reported in many other countries of the world, such as China (Bao and Zhang, 2020; Li et al., 2020), Bangladesh (Islam et al., 2021), Italy (Collivignarelli et al., 2020), Spain, France (Muhammad et al., 2020; Zambrano-monserrate et al., 2020), USA (Muhammad et al., 2020), Germany (Zambrano-monserrate et al., 2020), Brazil (Dantas et al., 2020), Kazakhstan (Kerimray et al., 2020), etc.

Several studies have shown the influence of the economic activities of a society on its air quality (Gautam, 2020b). NASA and the European Space Agency recently reported that there is a depletion in nitrogen-di-oxide (NO_2) levels in China after the economic slowdown following the complete lockdown of the country associated with COVID-19 infections (NASA Earth observatory, 2020). A similar effect was observed in history earlier during the collapse of the Soviet Union in 1991. There was a significant reduction in greenhouse gases attributed to the reduction in meat consumption fol-

lowing the economic slowdown (Schierhorn et al., 2019). A California study showed that economic indicators have a statistically significant impact on air pollution levels (Davis, 2012). Similarly, a study conducted in New Jersey showed that economic activity levels can be used as a potential marker for assessing exposure to traffic-associated pollutants in the absence of monitoring data (Davis et al., 2010).

There are many advantages for the public's perception of pollution being strongly correlated to actual levels of pollution. On the one hand, it prevents people from taking unnecessary health risks and generates public opinion against polluting emissions, forcing regulatory agencies to take corrective measures. On the other hand, it allows industries to judiciously make use of the assimilative capacity of the environment, resulting in net economic benefits to society. In the context of the importance of public perception in air pollution management, this study analyzes the change in air quality following the COVID-19 lockdown in India and its perception by the general public. Extensive data on actual air quality from 193 monitoring stations covering the whole country were taken from the repository of the regulatory agency. The public perception of air quality was obtained through an online questionnaire survey conducted among the general public answered by 1750 respondents. The data obtained were analyzed to obtain quantitative estimates of improvements in air quality and the relationship between Actual Air Quality (AAQ) and Perceived Air Quality (PAQ). The analysis results were used to arrive at conclusions regarding factors that were most influential in shaping perception.

2. Method

The general methodology adopted in the study is provided in Fig. 1.

2.1. Air quality data

Geography and population diversity are probably the most distinctive features of India, the second-most populous country in the world. From the Himalayan Mountains in the north to the Kanyakumari cape in the south and from the Thar Desert and salt marshes of the west to the humid forests of the northeast, the Indian mainland covers an area of 3,278,982 sq. km. The tropic of cancer divides the country roughly into two halves. The southern part of the country, being a peninsula, experiences milder variations in temperature, whereas the northern region experiences extremes in temperature (Singh, 2016).

Currently, there are approximately 231 continuous air monitoring stations in the country. These are connected to the web-based system, and the data are open to access for the public (CPCB, 2020a). These monitoring stations are maintained by the respective state pollution control boards. Considering the size of the country, the number of air quality monitoring stations is insufficient. The government has plans to strengthen the network in major cities in a phased manner (CPCB, 2020b). For this study, the air quality data for a total of 100 days (from 7 to 02-2020 to 16-05-2020) recorded at 193 air quality monitoring stations were downloaded from the Central Pollution Control Board (CPCB) website (<https://app.cpcbcr.com/ccr/#/caaqm-dashboard-all/caaqm-landing>). The pollutants considered in this study include PM_{10} , $\text{PM}_{2.5}$, SO_2 , NO_2 and O_3 . Furthermore, the air quality index (AQI), as calculated by CPCB, was also considered in this study (CPCB, 2014). CPCB calculates AQI by estimating the sub-indices of eight individual pollutants (PM_{10} , $\text{PM}_{2.5}$, NO_2 , SO_2 , CO , O_3 , NH_3 , and Pb) calculated using 24-hourly and 8-hourly (for CO and O_3) average values. AQI is calculated only where data for a minimum of three

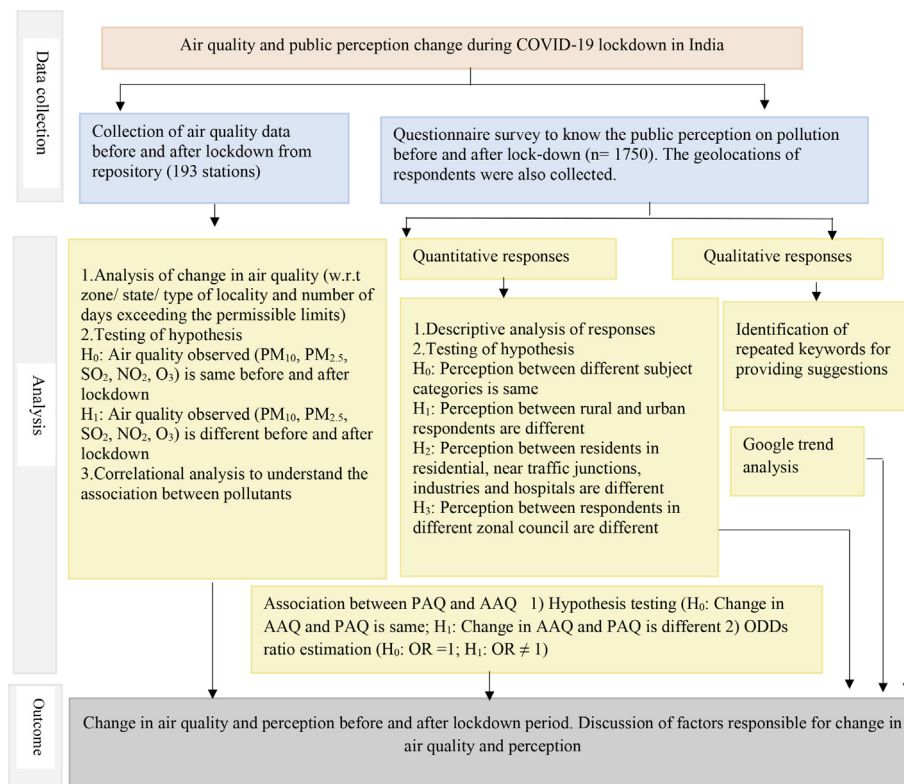


Fig. 1. General schematic sketch of the study.

pollutants is available. Out of the three pollutants, one should be necessarily either $PM_{2.5}$ or PM_{10} .

The period from 7 to 02-2020 to 22-03-2020 is considered the pre-lockdown period, and the period from 23 to 03-2020 to 16-05-2020 is considered the lockdown period in this study. The collected data were subjected to analysis for 1) changes in the concentration of air pollutants concerning different zones/states, 2) the number of days the pollution level exceeded the permissible levels before and during the lockdown, and 3) changes in the pollution level before and during lockdown concerning the type of locality (residential, traffic and industrial) and major cities (based on the population). The type of locality was decided based on the location of the monitoring station, whether in residential areas with minimum traffic, near major roads and traffic intersections or in industrial areas. Multivariate statistical analysis was performed using Pearson's correlation coefficient. Correlation coefficients are generally used to determine the degree of relationship between variables in pairwise comparisons (Núñez-Alonso et al., 2019), among which the Pearson correlation coefficient is the most commonly used method in linear regression. In this study, it is used to measure the strength of the relationship between selected pollutants before and after the lockdown period.

2.2. Perception survey

Residents from all across the country were asked to complete the questionnaire ($n = 1750$). The survey was conducted between 17 and 4-2020 and 27-5-2020. A total of 16 survey questions were asked. The entire survey was divided into three sections: 1) location details, 2) perception of improvement of air quality, visibility, health effects and sources, and 3) willingness to maintain air quality. Survey questions in sections 2 and 3 were asked on the rating scale and Likert scale. For example,

"Rate the air quality in your locality before the lockdown period?" 1 = Poor to 5 = Good.

"Is there improvement in visibility in your locality?" No improvement, Slight improvement, Moderate improvement, Significant improvement and Don't know.

"I will actively be involved in maintaining the current status of the environment" Strongly agree, Agree, Undecided, Disagree and Strongly Disagree.

The questionnaire for the online survey is generated and circulated through Google forms (included as [supplementary material in Appendix A](#)). The questionnaire had the option of collecting the Geolocations of responders with their permission for plotting the results easily in ArcGIS (version 10.5). All statistical analyses were performed using SPSS 20. Descriptive statistics were used to present the respondents' demographics and responses to the questionnaire. Independent sample non-parametric tests were conducted to understand the difference in opinion of the respondents belonging to different categories. Test of significance was performed using Chi-square (χ^2) and t-tests. The level of statistical significance was tested at 95% confidence level ($P \leq 0.05$). The strength of the relationship between the two fields was determined using "Effect size", calculated with Cramer's V (ES). It is used to measure how strongly the categorical fields selected for the analysis are associated. When $ES \leq 0.2$, the fields are weakly associated; $ES 0.2 < ES \leq 0.6$, the fields are moderately associated and when $ES > 0.6$, the fields are strongly associated (Sullivan and Feinn, 2012).

The perceptions were analyzed based on 1) location (rural or urban), 2) type of locality (residential, near traffic junctions, near industries and near hospitals), 3) different zonal councils (western zonal council (W), southern zonal council (S), northern zonal council (N), eastern zonal council (E) and central zonal council (C)), and 4) major cities (selected based on the population and pollution levels). Zonal councils in India were set up vide Part-III of the States

Reorganization Act, 1956, and this classification was made to establish an advisory council “to develop the habit of cooperative working” among the states in the council. Councils were created to develop healthy inter-state and Center-state relationships by solving the inter-state issues and balancing the socio-economic development of the corresponding zones (Government of India, 2019). States under each council are provided in the [supplementary material \(Appendix- B\)](#).

The perception of air quality is often influenced by the media (Murukutla et al., 2019). To find the effect of media on air quality perception, an analysis was conducted using “Google trends”. Keywords such as “Air Quality”, “Air Quality Index” “AQI” and “Air Pollution” were used to analyze the frequency of discussions on air quality by the media. Frequent discussions on the topic by media may unduly affect the perception.

2.3. Qualitative response analysis

The question asked in the qualitative survey part is “Please give your suggestions for maintaining the air quality after the lockdown period”. Qualitative response analysis was conducted by the process of identification, examination and finally interpreting the frequently repeated keywords in the textual data and based on the frequency of repetition of the keywords. The most frequently repeated keywords are provided in the [supplementary material \(Appendix- C\)](#). Based on this analysis, suggestions are given to maintain the air quality after the lockdown period.

2.4. Relationship between AAQ and PAQ

The perception on air quality was collected on a rating scale of 1 to 5. Similarly, the AQI and the concentrations of the individual pollutants were also converted to rating scales as per breakpoint scales proposed by CPCB (CPCB, 2014) given in [Table 1](#). Both values were subjected to a test of significance using SPSS 20 to establish the relationship between PAQ and AAQ.

Furthermore, the odds ratio (OR) was also used to express the strength of the association between AAQ and PAQ. The odds ratio is a statistic that is used to measure the association between the exposure and the outcome (Szumilas, 2010).

Case 1: Association between exposure and perception.

The odds that people perceive improvement in air quality when there is actual improvement in air quality, was compared to the odds that they perceive an improvement even in the absence of any significant improvement in actual air quality, using OR. The responses of people from two states, one where there was a significant improvement in air quality (Delhi) and the other with nominal improvement in air quality (Telangana), were used to calculate the OR.

Case 2: Association between air quality and health effects.

The odds that people experience improvements in health when their perceived air quality improve, was compared to the odds that people experience improvements in health even when they do not perceive any improvements in air quality. The calculations were based on the responses to a question on improvement in health

(Do you feel an improvement in your health due to improvement in air quality after the lock-down? A) No improvement, B) Slight improvement, C) Moderate improvement, D) Significant improvement, E) Not relevant for me). Those respondents who have mentioned “not relevant for me” were not considered for the analysis. The odds ratio was calculated as in equation (1).

The confidence level (CL) and confidence interval (CI) of the OR was calculated as per Tenny and Hoffman, (2021).

$$OR = \frac{(A/C)}{(B/D)} \quad (1)$$

where,

Case 1. A- number of people who perceived significant improvement in air quality from an area (Delhi) where there was a significant improvement in AAQ.

C- number of people who perceived no/slight improvement in air quality from an area (Delhi) where there was a significant improvement in AAQ.

B- number of people who perceived significant improvement in air quality from an area (Telangana) where there was only nominal improvement in AAQ.

D- number of people who perceived no/slight improvement in air quality from an area (Telangana) where there was only nominal improvement in AAQ.

When OR is > 1, it indicates that the perception is dependent on improvement in the air quality. The higher the value of OR, the stronger the dependence.

Case 2. A- number of people who perceived significant improvement in air quality and significant improvement in health.

C- number of people who perceived significant improvement in air quality and no improvement in health.

B- number of people who perceived no improvement in air quality, but significant improvement in health.

D- number of people who neither perceived any improvement in air quality nor any improvement in health.

3. Results

3.1. Actual air quality

The overall country averages for PM₁₀ calculated using the interpolated values were 116 µg/m³ and 70 µg/m³ before and after lockdown, respectively. Statistical analysis using a *t*-test showed a significant difference in PM₁₀ levels before and after lockdown, with *p* < 0.05. [Fig. 2](#) (a-c) shows PM₁₀ levels before and after lockdown and improvement in its levels during the lockdown. The overall country averages calculated using the interpolated value for PM_{2.5} are 56 µg/m³ and 31 µg/m³ before and after lockdown, respectively. Statistical analysis using a *t*-test showed a significant difference in PM_{2.5} levels before and after lockdown, with *p* < 0.05. [Fig. 3](#) (a-c) shows PM_{2.5} levels before and after lockdown and improvement in its levels during the lockdown. The country-

Table 1
Breakpoints for AQI Scale 0–500 (all units are in µg/m³) (CPCB, 2014).

| AQI Category | PM ₁₀ 24 hr | PM _{2.5} 24 hr | NO ₂ 24 hr | SO ₂ 24 hr | O ₃ 8 hr | Rating scale |
|--|---------------------------|----------------------------|--------------------------|--------------------------|------------------------|--------------|
| Good (0–50) | 0–50 | 0–30 | 0–40 | 0–40 | 0–50 | 5 |
| Satisfactory (51–100) | 51–100 | 31–60 | 41–80 | 41–80 | 51–100 | 4 |
| Moderately Polluted (101–250) | 101–250 | 61–90 | 81–180 | 81–380 | 101–168 | 3 |
| Poor (201–300) | 251–350 | 91–120 | 181–280 | 381–800 | 169–208 | 2 |
| Very Poor & Severe (301–400) & (401–500) | 351–430 & 430 + | 121–250 & 250 + | 280–400 & 400 + | 801–1600 & 1600 + | 209–748 & 748 + | 1 |

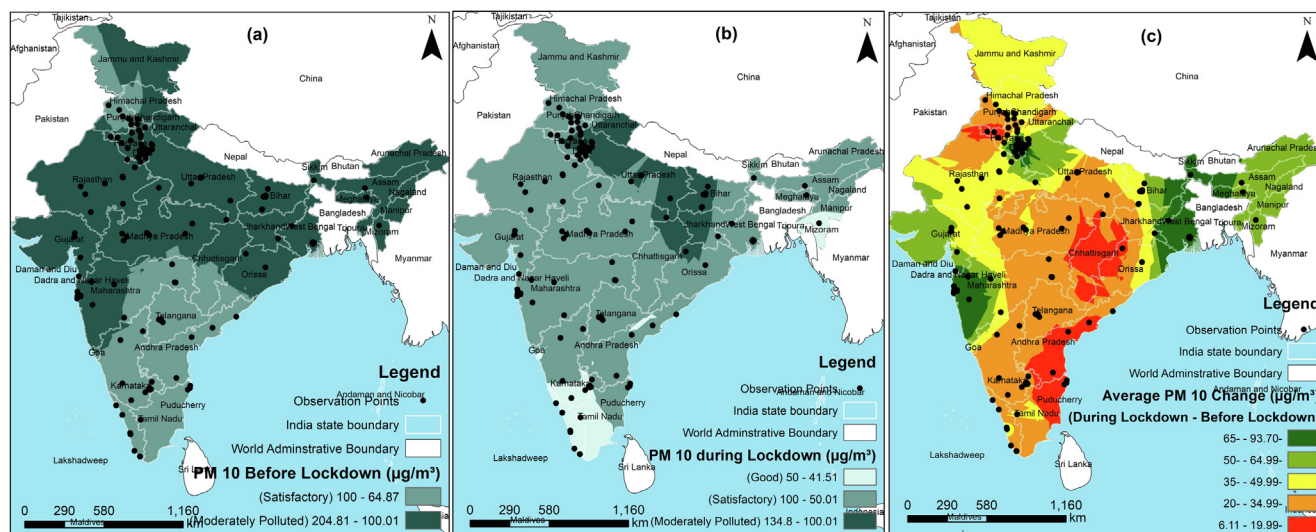


Fig. 2. a) PM_{10} level before lockdown, b) PM_{10} level after lockdown, c) Change in PM_{10} level.

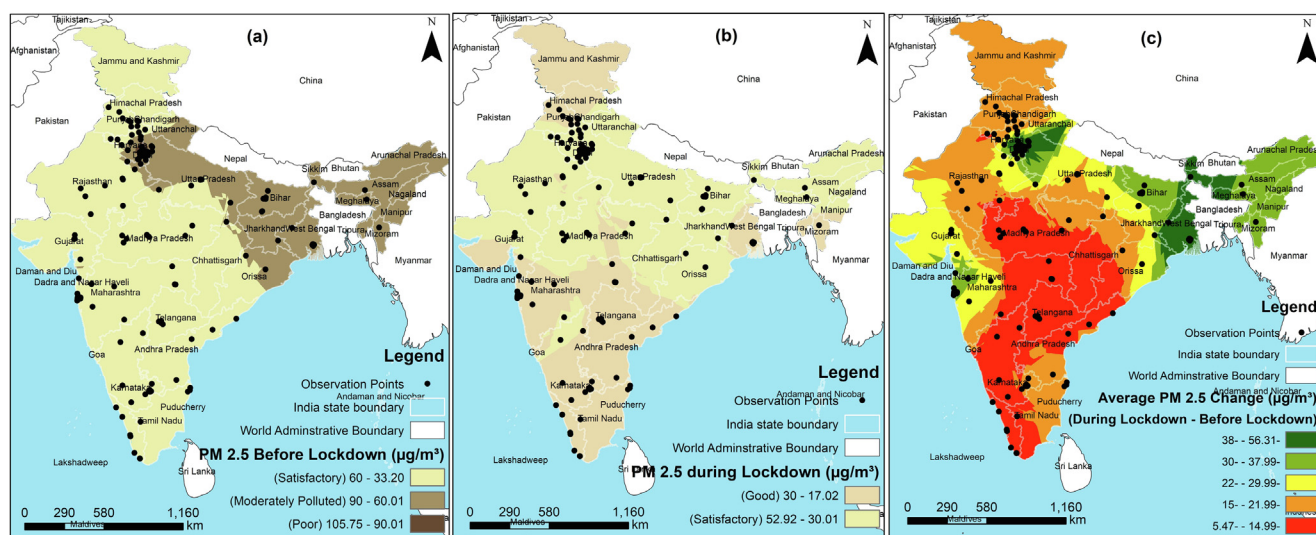


Fig. 3. a) $PM_{2.5}$ level before lockdown, b) $PM_{2.5}$ level after lockdown, c) Change in $PM_{2.5}$ level.

wide average reduction percentages for PM_{10} (44%) and $PM_{2.5}$ (51%) were significantly different ($p < 0.05$), with $PM_{2.5}$ having a higher reduction. Concerning the percentage improvement in air quality calculated with the actual data of $PM_{2.5}$ and PM_{10} , West Bengal showed the highest (64%) improvement in air quality. Orissa showed the lowest improvement in air quality (10%) for $PM_{2.5}$ levels. In the case of Haryana, Uttar Pradesh and Bihar, the percentage reduction of $PM_{2.5}$ were higher than the percentage reduction of PM_{10} .

The overall country averages using the interpolated value for NO_2 were $30.45 \mu g/m^3$ and $14.64 \mu g/m^3$ before and after lockdown, respectively. Statistical analysis using a t -test showed that there was a significant difference in NO_2 levels before and after lockdown, with $p < 0.05$. Fig. 4 (a-c) shows NO_2 levels before and after lockdown and improvement in NO_2 levels during the lockdown. Among the states, the lowest level of NO_2 before the lockdown was observed in the states of Jammu and Kashmir, Punjab, Kerala, Tamil Nadu and Andhra Pradesh. Similar to other pollutants, such as PM_{10} and $PM_{2.5}$, the highest decrease percentage in NO_2 levels as a result of lockdown was observed in West Bengal.

The overall country averages using the interpolated value for SO_2 were $14 \mu g/m^3$ and $11 \mu g/m^3$ before and after lockdown, respectively. Statistical analysis using a t -test showed that there was a significant difference in SO_2 levels before and after lockdown with $p < 0.05$. Fig. 5 (a-c) shows SO_2 levels before and after lockdown and improvement in SO_2 levels during the lockdown. During the lockdown period, the lowest SO_2 levels were observed in the southern states, Kerala and Tamil Nadu.

The overall country averages using the interpolated values for O_3 were $35 \mu g/m^3$ and $37 \mu g/m^3$ before and after lockdown, respectively. Statistical analysis using t -test showed that there is no significant difference in O_3 level before and after lockdown with $p > 0.05$. Fig. 6 (a-c) shows O_3 levels before and after lockdown and improvement in O_3 levels during the lockdown. The highest average O_3 concentration before the lockdown was observed in some areas of Rajasthan and Madhya Pradesh. During the lockdown period, a decrease in O_3 concentration was observed in the southern, some parts of the western, and some northeastern states. At the same time, Madhya Pradesh, some areas of Rajasthan, a few Northern states, and West Bengal showed slight increases in O_3 concentration.

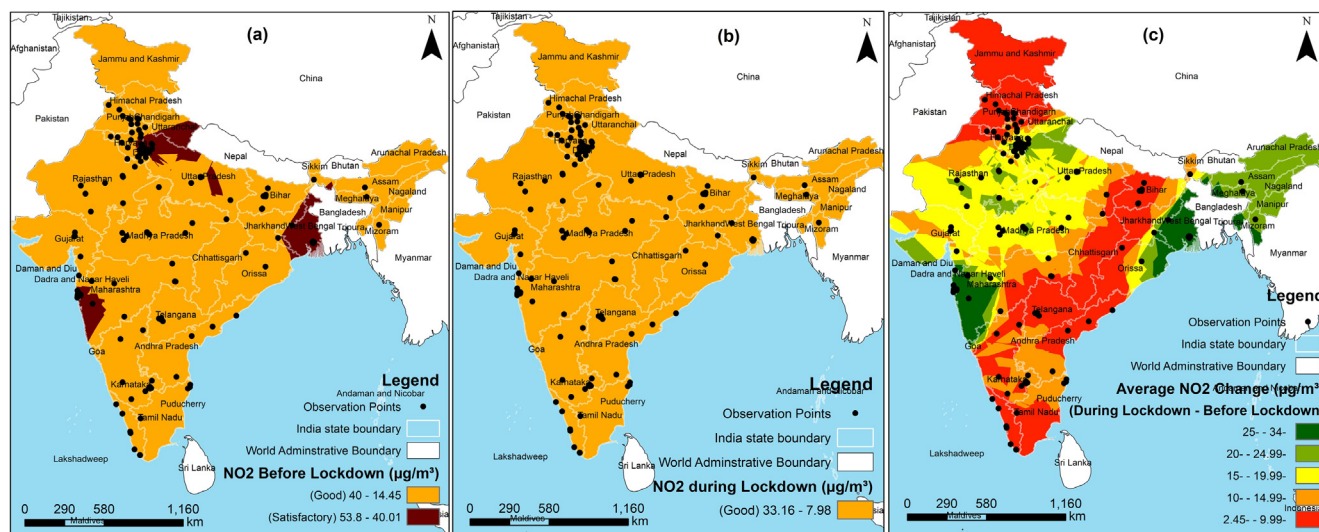


Fig. 4. a) NO₂ level before lockdown, b) NO₂ level after lockdown, c) Change in NO₂ level.

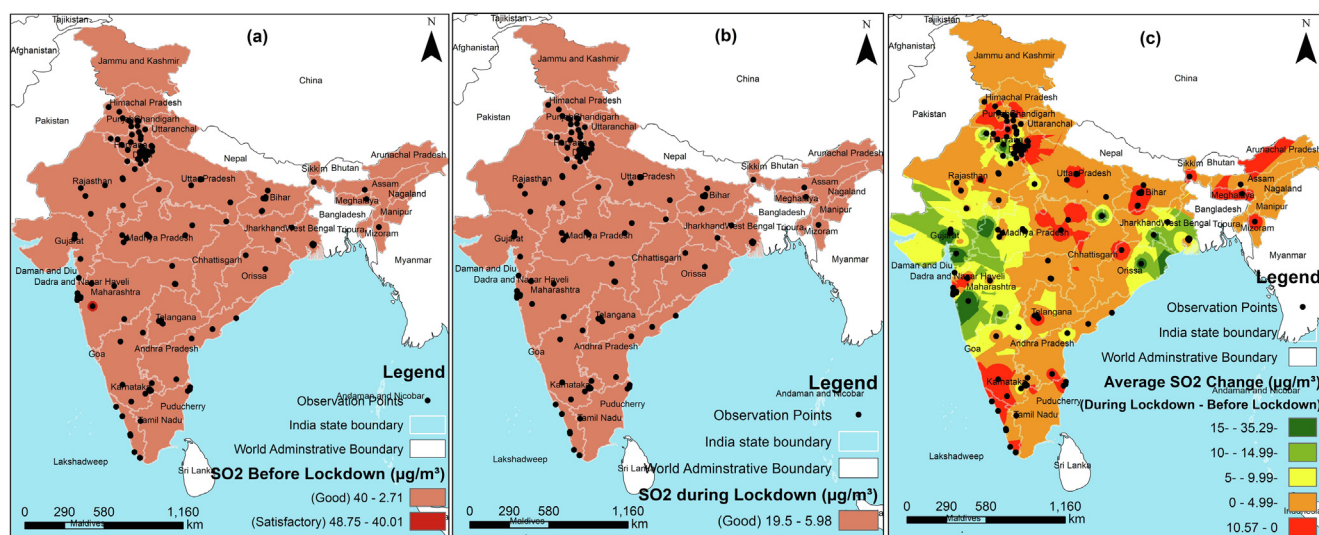


Fig. 5. a) SO₂ level before lockdown, b) PM SO₂ level after lockdown, c) Change in SO₂ level.

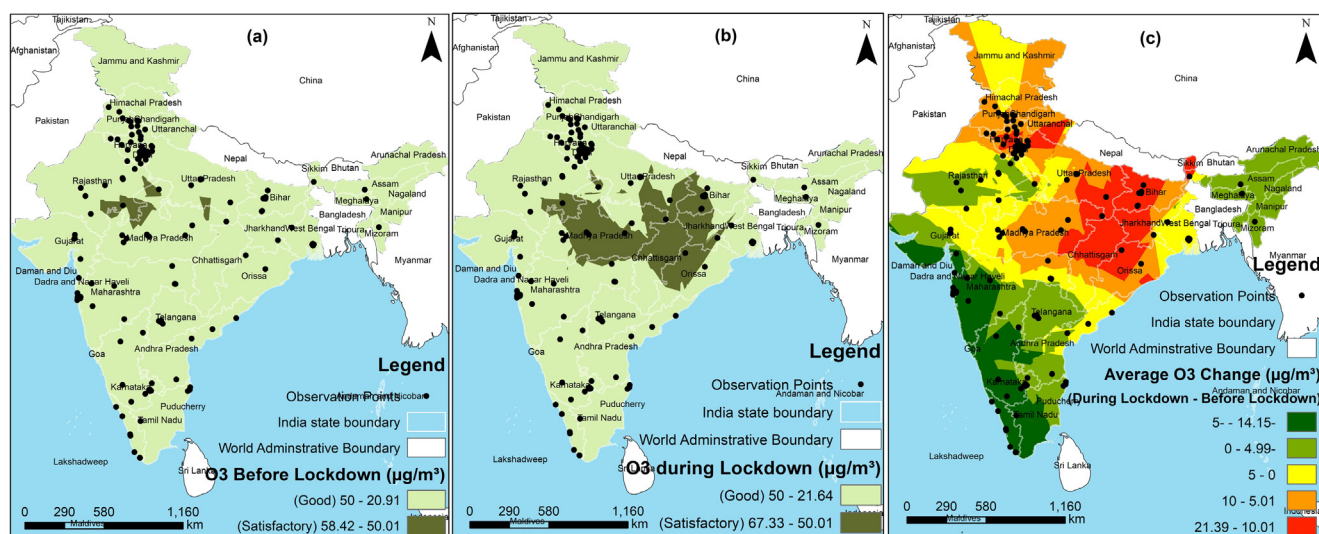


Fig. 6. a) O₃ level before lockdown, b) O₃ level after lockdown, c) Change in O₃ level.

tration levels. The highest increase was observed in the eastern regions and in the northern states of Delhi, Uttaranchal, Haryana, and Uttar Pradesh, where the PM₁₀ concentrations were higher before the lockdown period.

The country experienced an overall increase in AQI levels, as shown in Fig. 7. The highest improvement in AQI was seen in West Bengal (61.89%), followed by Arunachal Pradesh (47.80%) and Meghalaya (47.58%). The least change was observed in Orissa (3.55%). The AQI values in Orissa before and after lockdown were 132.49 and 127.78, respectively. Even before lockdown, the AQI in the southern states was in the satisfactory range. Among the major cities, the greater percentage reduction in AQI was in Jaipur, followed by Kolkata, Mumbai, Pune and New Delhi. The lowest reduction was observed in Chennai. The other major cities, such as Bangalore, Hyderabad and Ahmedabad, had intermediate percentage reductions in AQI values. Although the lowest AQI value before the lockdown was observed in Chennai, the lowest value after the lockdown was found in Jaipur. Additionally, the highest value before and after the lockdown was observed in New Delhi.

The interpolated values of pollutant concentrations were compared with NAAQS to determine the number of days when it exceeded the permissible limits (Figs. 8 & 9). It was observed that gaseous pollutants (NO₂, SO₂ and O₃) were within the permissible limits before and after lockdown. In the case of West Bengal, Telangana, Meghalaya, Maharashtra, Kerala, Karnataka, Chandigarh and Andhra Pradesh, there was no day when the state average value exceeded the permissible limits as prescribed by CPCB in the case of PM₁₀ after the implementation of lockdown. The percentage reduction of pollution in all three categories of areas (traffic, residential, and industrial) was approximately 40% after the implementation of COVID-19 lockdown, as shown in Fig. 10. In the case of NO₂ and SO₂, the ambient air concentrations were within the limits in all these cities even before lockdown. The lockdown further reduced their concentrations by 30.45 µg/m³ to 14.64 µg/

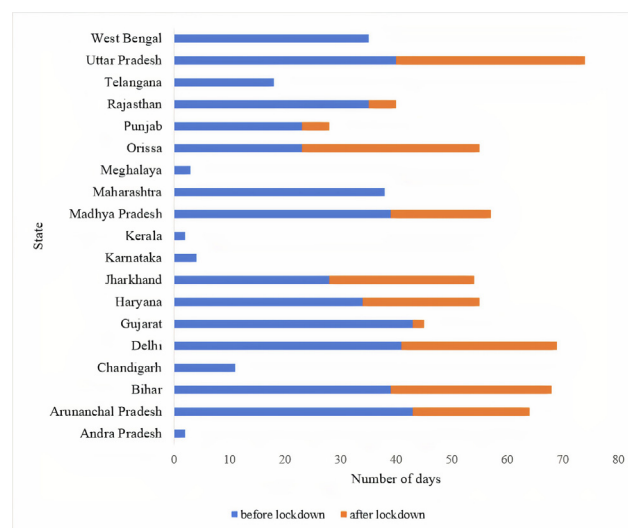


Fig. 8. Number of days exceeding the permissible limits – PM₁₀.

m³ for NO₂ and 14 µg/m³ to 11 µg/m³ for SO₂. Their values exceeded the permissible limits (80 µg/m³) for a very few days (<1% days). Ozone, on the other hand, showed a reverse trend due to lockdown. In New Delhi, Kolkata, Chennai and Hyderabad, the concentration of ozone increased, ranging from 3.8 to 38.3% as in Fig. 11.

Correlation analysis can be used to explore the associations between a pair of pollutants. Highly correlated concentrations are indicative of common sources for both pollutants (Binaku and Schmeling, 2017; Ebqa'ai and Ibrahim, 2017; Núñez-Alonso et al., 2019; Zhu et al., 2017). The values of the Pearson coefficient of the pollutant pairs before and after the lockdown period are given in Table 2.

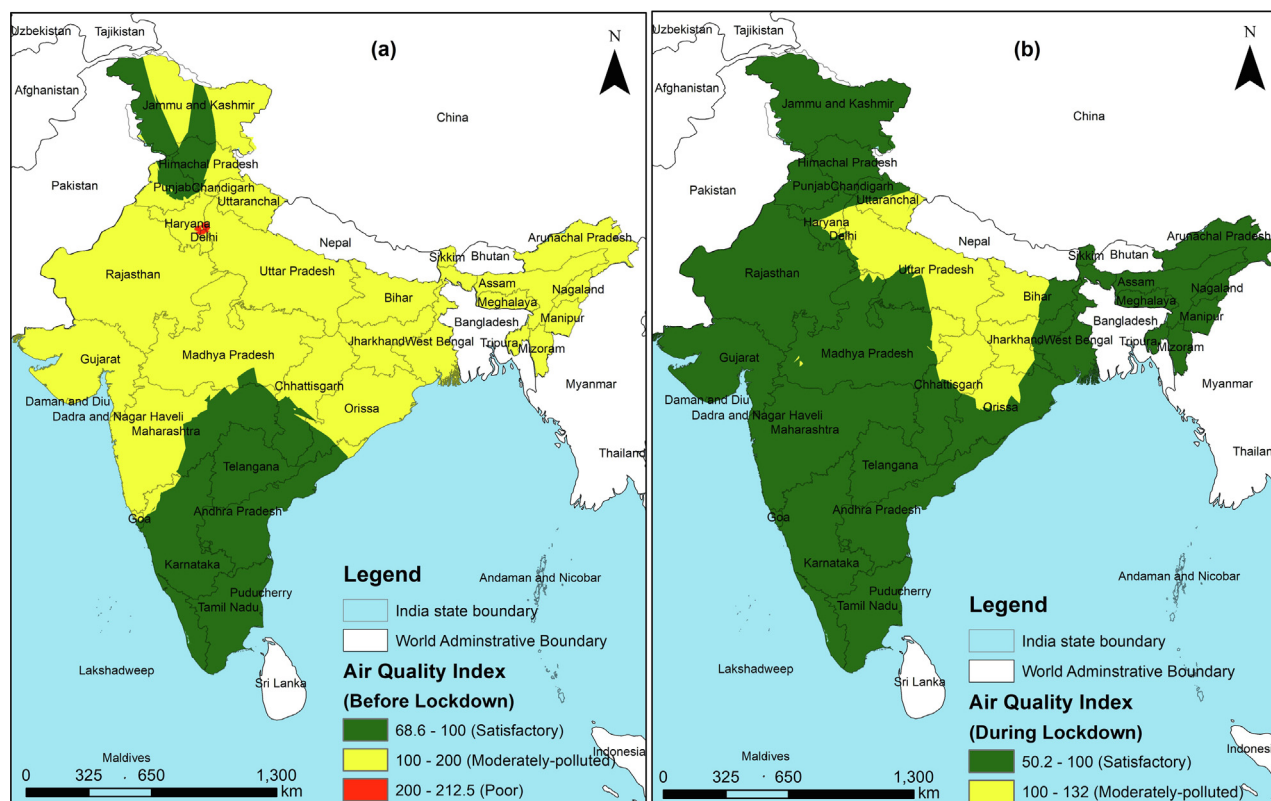


Fig. 7. AQI before and after lockdown.

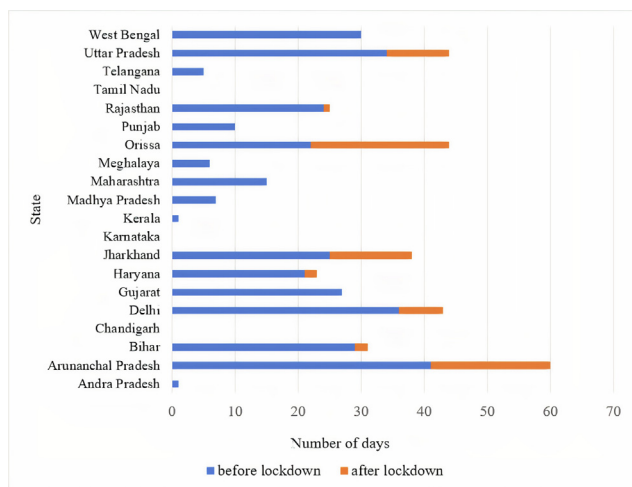


Fig. 9. Number of days exceeding the permissible limits – PM_{2.5}.

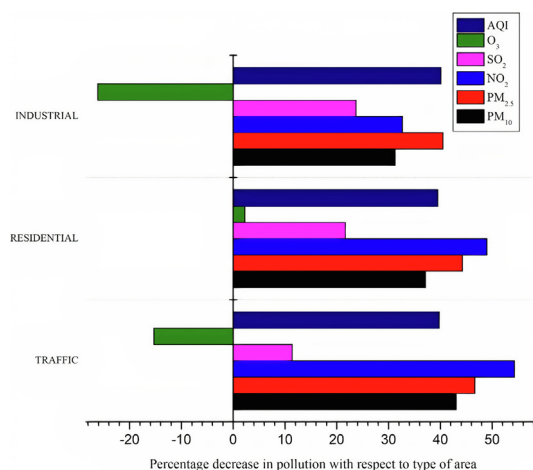


Fig. 10. Percentage decrease in pollutant levels based on the type of area.

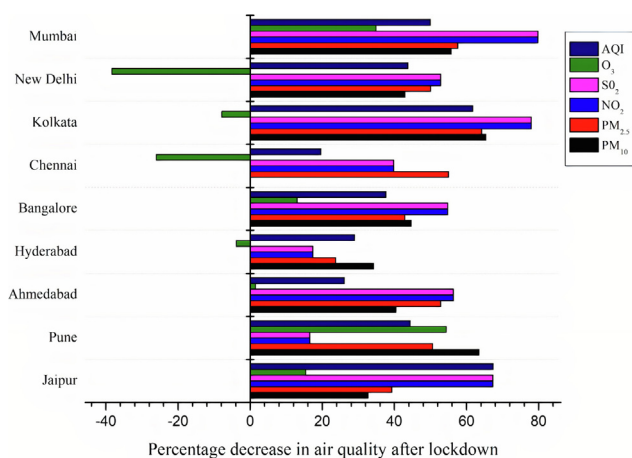


Fig. 11. Percentage decrease in pollutant levels after the lockdown in major cities.

3.2. Perceived air quality

On conducting χ^2 tests on the responses obtained from rural and urban populations, a significant difference in opinion was noticed between them; χ^2 (2, N = 1750) = 43.99, $p < 0.05$. Urban

responders felt a higher improvement in air quality during the lockdown (64% to 49%). The observed effect size was Cramer's $V = 0.2$, indicating a small effect size in the difference in perception. This shows that although there is a significant difference in opinion, the people in both rural and urban environments have perceived improvement in air quality. Considering the different types of localities (residential, traffic, industrial), a significant difference in opinion was observed, χ^2 (2, N = 1395) = 18.987, $p < 0.05$. The observed effect size in this scenario was much smaller (Cramer's $V = 0.1$). The order of improvement of air quality perception among different localities was Industries > Near to traffic junctions > Residential > Near to hospital, as shown in Fig. 12. Nearness to the hospital was considered a separate category expecting more traffic near hospitals due to the pandemic situation. More than half of the respondents in all major cities perceived improvement in air quality: Delhi (100%), Ahmedabad (85%), Chennai (83%), Mumbai (80%), Bangalore (65%), Jaipur (66%) and Hyderabad (54%).

A non-parametric (independent sample Kruskalwallis) test was conducted to establish differences in opinion among different zones in India. In the case of visibility, the opinion on improvement was found to be similar on pairwise comparison across all the zones in the country, except in the case of Southern zonal council vs. Northern zonal council and Southern zonal council vs. Central zonal council, with a p-value of < 0.05 . Similarly, in the case of perception on the improvement of health, significant differences in responses were obtained from the North Eastern vs. Central and Western zonal council and Northern vs. Central zonal council, with a p-value of < 0.05 . In the case of indoor air quality (IAQ), a significant difference in opinion was obtained from the northern and southern zonal councils, as in the case of visibility. The mean rating (on a five-point scale) of air quality perception in the case of rural areas increased from 3.5 to 4.3, whereas in the case of urban areas, it increased from 2.9 to 4.12. The improvement in the perception of air quality is shown in Fig. S1. In a zone-wise comparison, people from all zones felt air quality to be 'excellent' after lockdown, as shown in Fig. S2. Responses from major cities in India were analyzed separately, and it was found that the mean perception of Ahmedabad changed from 2.4 to 4.1, Bangalore and Hyderabad changed from 2.92 to 4, Chennai changed from 2.7 to 4.2, Delhi changed from 2.2 to 4.5, Jaipur changed from 2.8 to 4.3, Kolkata and Mumbai changed from 2.6 to 4.2, and Pune and Surat changed from 3 to 4, as represented in Fig. S3. This indicates that respondents from major cities across India perceived improvement in air quality during this lockdown period. The obtained perception scales and geolocations were directly subjected to geo-spatial analysis using ArcGIS version 10.5. The maps in Fig. 13 (a-c) indicate the perception before and after lockdown and the change in perception due to the lockdown. Fig. S4-6 indicates the district average perception before and after lockdown and the change in perception due to the lockdown.

The major sources of pollution as perceived by the respondents before the lockdown was Vehicular Pollution > Road dust > Construction works > Industries > Roadside burning > Burning of agricultural waste > Power plant. However, after lockdown, the order was Household emissions > Solid waste burnings > Traffic > None (there is no source for pollution) > Industrial activities > others. Several other studies have also shown that there is a significant increase in household emissions during the COVID-19 lockdown. This is due to increase in confined indoor activities and increased usage of household fuels for cooking and heating (Beig et al., 2020; Li et al., 2021; Zhang et al., 2022). In India, a 12% increase in usage of LPG was observed during the lockdown period which could have contributed to increased household emissions (Singh et al., 2020). The frequency of response is provided in Table S1. Other factors included burning

Table 2
Correlation among the selected pollutants before lockdown (N = 158).

| | PM ₁₀ | PM _{2.5} | NO ₂ | SO ₂ | O ₃ |
|-------------------|----------------------|----------------------|--------------------|---------------------|----------------|
| PM ₁₀ | 1 | | | | |
| PM _{2.5} | 0.880 ^{**b} | 1 | | | |
| NO ₂ | 0.473 ^{**b} | 0.555 ^{**b} | 1 | | |
| SO ₂ | 0.212 ^{**b} | 0.228 ^{**b} | 0.107 ^b | 1 | |
| O ₃ | −0.057 ^b | −0.061 ^b | 0.138 ^a | 0.043 ^b | 1 |
| | 0.247 ^{**a} | 0.214 ^{**a} | 0.003 ^a | 0.0860 ^a | |

^{**} Correlation is significant at the 0.01 level (2-tailed).
^b Before lockdown,
^a After lockdown.

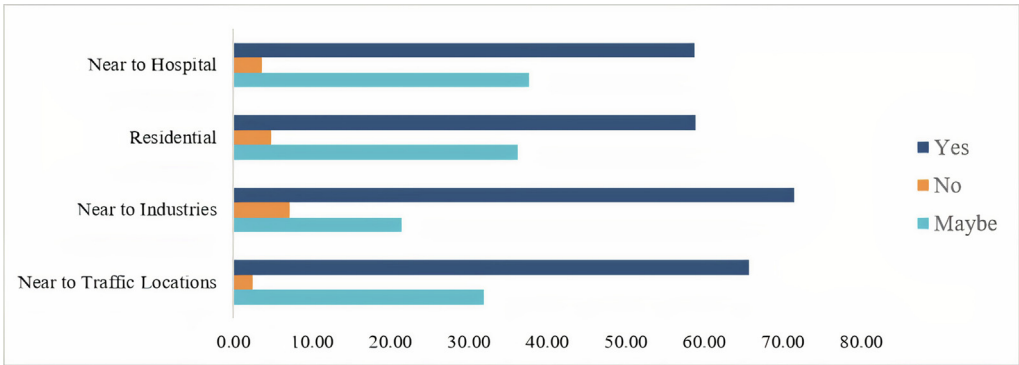


Fig. 12. Perception based on residence.

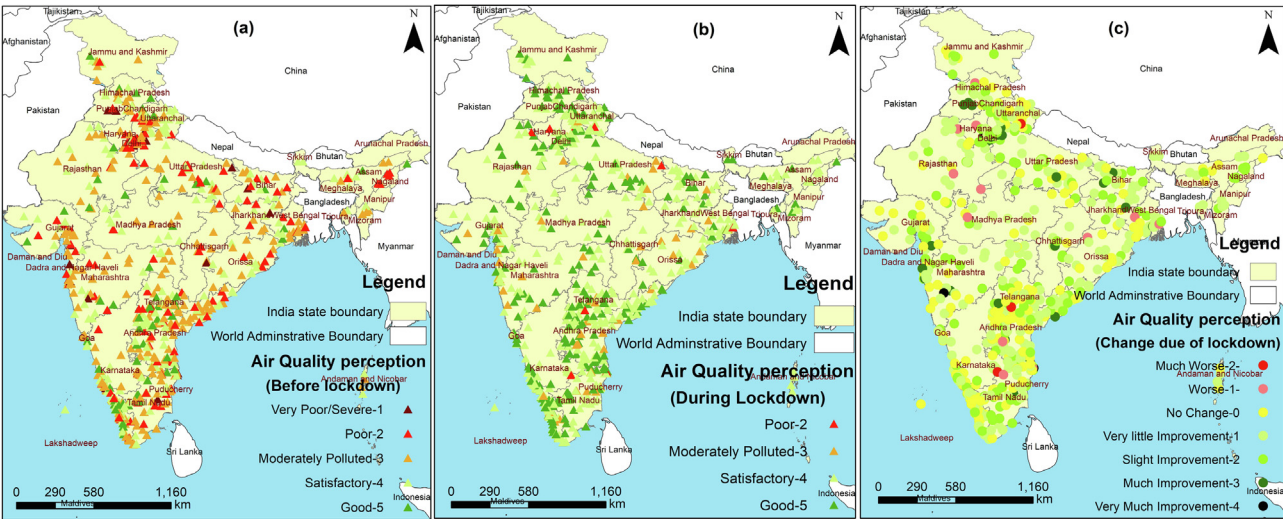


Fig. 13. (a) Perception of air quality before lockdown, (b) Perception of air quality after lockdown, (c) Change in perception of air quality.

of crackers, spraying of disinfectant chemicals and smoking. The perception of sources among different localities and zonal councils is given as [supplementary material \(Fig. S7–S10\)](#).
The results from Google Trend Analysis (<https://trends.google.com/trends/?geo=US>) showed that terms related to air pollution ('air quality', 'air quality index', 'air pollution', 'AQI') were trending from October to December 2019, as shown in [Fig. 14](#). As per the Google Trend Analysis, maximum searches occurred in North Indian states such as Delhi, Haryana, Uttar Pradesh, Punjab, Uttarakhand, and Himachal Pradesh. October to December is the period every year North and North-West India face severe air pollution

due to stubble burning compounded by meteorological conditions ([Patel, 2019; Rizwan et al., 2013](#)). The trend that declined drastically after the annual pollution episode continued decreasing to the lockdown period, albeit at a smaller rate, except for a small spike on 22/03/2020, the day when the *Janata* curfew was implemented.

3.3. Relationship between PAQ and AAQ

Our perception survey showed that approximately 60% of the respondents perceived improvement in air quality during the

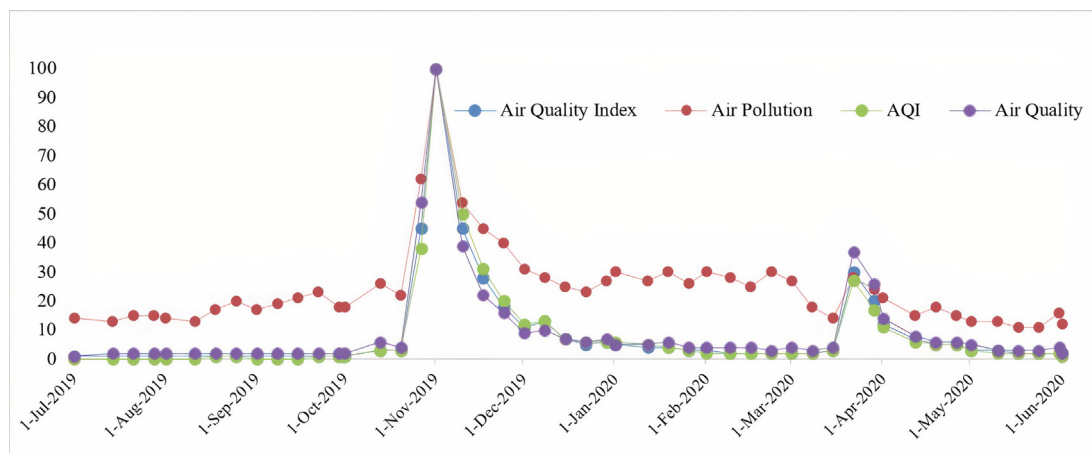


Fig. 14. Google trend analysis.

COVID-19 lockdown compared to the pre-lockdown period. The analysis of the air quality monitoring data showed that from the pre-lockdown to lockdown period, the AQI improved by 40% in the country. To have a quantitative comparison, the perceived air quality was obtained on a rating scale from 1 to 5 (Poor to Good). The pollutant concentrations were converted to the same rating scale (1 to 5) as per the breakpoints proposed by CPCB. The results of the paired *t*-test are provided in Table 3.

Odds ratio (OR) is often used in medical statistics to indicate the probability that an outcome will occur under a specific exposure compared to the probability that an outcome will occur without the exposure (Szumilas, 2010). It is extensively used to analyze the relationship between exposure to pollutants and its health effects (Baxter et al., 2010; Klompmaker et al., 2019; Lee et al., 2014; Yorifuji et al., 2014). It is also used in air quality perception studies (Malenka et al., 1993; VanderWeele and Vansteelandt, 2010; Vodá et al., 2020). To quantify the change in air quality vis à vis the perception, responses from a city with one of the highest reductions in pollution (Delhi – 72 responses) and an area where there was only a small reduction in pollution after lockdown (Rural Telangana – 39 responses) were used to calculate the odds ratio. To quantify the association between air quality and health, responses of people who perceived significant health improvement (850 responses) and no improvement in health (344 responses)

due to improvement in air quality during the lockdown, were used. The details of the responses are given in Table 4. The OR calculated for cases 1 and 2 are 17 (95% CI: 6.42, 47.04) and 5.2 (95% CI: 2.69, 10.01), respectively.

4. Discussion

4.1. Actual air quality

Compared to other states in India, many of the southern states had low PM₁₀ and PM_{2.5} levels before and after the lockdown period. However, while considering the improvement in air quality in absolute terms following lockdown, the southern states showed lower improvement compared to the other states. Though the improvement in absolute terms was less, overall better air quality was observed in the southern states. The values of PM_{2.5}/PM₁₀ were found to be greater than > 0.5 in North East states such as Arunachal Pradesh and Meghalaya, which shows that a major portion of PM₁₀ was PM_{2.5}. The North-East states are less industrialized and scarcely populated, and this observation points to the long-distance transport of PM_{2.5} from other places.

The average NO₂ level in the country was more than halved during the lockdown period. Vehicles are the major contributor of NO₂ in ambient air (Ramachandran et al., 2013; US EPA, 2019), and a large reduction in NO₂ levels are expected. On March 24th, 2020, soon after the implementation of lockdown, an approximately 60% reduction in traffic was observed. In Delhi, the morning traffic congestion in 2019 was between 50 and 80 %, but it was reduced to single-digit values ranging from 0 to 6 %. Similarly, in Bombay, the traffic congestion in 2019 during morning rush hours was 60 to 80%, and it decreased to < 5%. A similar trend was observed throughout the lockdown period (Tom Tom Traffic Index, 2020). In Howrah and Kolkata (West Bengal), all the monitoring stations in the traffic zone recorded a 66 to 85% reduction of NO₂. Similar reductions were noticed in the high traffic zones of Noida, Greater Noida and Ghaziabad (52–74%), Haryana (74%), Kanpur (54–66%), Chennai (67%), Udaipur (68%), Kota (57%), Jodhpur (55%), Jaipur (66%), Mizoram (74%), Mumbai (67–88%), Nagpur (60%), Navi Mumbai (85%), Tirupati (76%), and Thiruvananthapuram (65%). Reductions were also observed in traffic zones of Delhi (50 to 75%), Madhya Pradesh (60 to 70%), and Bangalore (58–80%). Among petrol and diesel vehicles, a higher contribution of NO₂ is from diesel vehicles (European Union, 2019). The fact that a major portion of the vehicles registered in the country is diesel vehicles (Government of India, 2015) could also have contributed to the higher reduction of NO₂. In Delhi, compressed natural gas (CNG)

Table 3
Results of paired sample *t*-test.

| Combinations | p-value |
|---|---------|
| Pair 1 AQ BL- AQ AL | 0.01 |
| Pair 2 AP BL- APAL | 0.00 |
| Pair 3 APBL- AQ BL | 1.00* |
| Pair 4 AP AL- AQ AL | 0.48* |
| Pair 5 AP BL - PM ₁₀ BL | 0.49* |
| Pair 6 AP AL - PM ₁₀ AL | 0.33* |
| Pair 7 AP BL - PM _{2.5} BL | 0.05 |
| Pair 8 AP AL - PM _{2.5} AL | 0.03 |
| Pair 9 AP BL - NO ₂ BL | 0.00 |
| Pair 10 AP AL - NO ₂ AL | 0.00 |
| Pair 11 APBL - SO ₂ BL | 0.00 |
| Pair 12 AP AL - SO ₂ AL | 0.00 |
| Pair 13 AP BL - O ₃ BL | 0.00 |
| Pair 14 AP AL - O ₃ AL | 0.00 |
| Pair 15 PM ₁₀ BL - PM ₁₀ AL | 0.00 |
| Pair 16 PM _{2.5} BL - PM _{2.5} AL | 0.00 |
| Pair 17 NO ₂ BL - NO ₂ AL | 0.16* |
| Pair 19 O ₃ BL- O ₃ AL | 0.33* |

* p > 0.05 – There is no significant difference between the pairs: AQ – Actual air quality, AP – Air quality perception, BL- Before lockdown, AL- After lockdown.

Table 4
Inputs for the determination of odds ratio.

| Case | A | B | C | D | OR |
|------|-----|----|-----|----|-----|
| 1 | 57 | 7 | 15 | 32 | 17 |
| 2 | 242 | 13 | 147 | 41 | 5.2 |

vehicles constitute a significant portion of the vehicles on the road. Studies have confirmed that although CNG vehicles emit fewer pollutants than petrol and diesel vehicles concerning PM₁₀, PM_{2.5} and SO₂, there is not much reduction in NO₂ emissions (Narain and Krupnick, 2007). India is the world's largest emitter of SO₂, and its emissions are mainly from 45 hotspots in the country (Shagun Kapil, 2019). Out of the 45 hotspots, 43 have coal-based electricity generation. In Talcher Coalfields, Orissa, an approximately 50% reduction of SO₂ was observed, although the coal mines were still operational, albeit at reduced capacity. A significant reduction in SO₂ was also observed in many industrial belts across the country. For example, in Jahangirpuri- Delhi (70%), Pusa- Delhi (50%), GIDC, Ankleshwar- Gujarat (78%), Phase-4 GIDC, Vatva- Gujarat (83%), Industrial belt near to Chhatrapati Shivaji International Airport- Mumbai (83%), Mahape, Navi Mumbai (59%), and RIICO Industrial Area III- Bhiwadi (72%).

As per the 2011 census data, the most populated cities in India are Mumbai, Delhi, Bangalore, Hyderabad, Ahmedabad, Chennai, Kolkata, Surat, Pune and Jaipur. Except for Surat, data were available for all these cities. For PM_{2.5}, most of the cities showed >50% reduction in concentration after the start of lockdown. In all the cities, the mean concentration fell below the CPCB standards for ambient air, and the daily average values stayed within limits for approximately 95% of days. Similar observations were also made in the case of PM₁₀. Its mean concentration fell to within the CPCB limits in all cities except Delhi, where it just crossed the limit. The concentration decreased by approximately 47% in these cities, and the values remained within the limit for approximately 91% of the days.

The reduced traffic and restricted industrial activities have probably resulted in the reduction in PM_{2.5}, CO and NO₂ concentrations reported from different countries of the world during COVID-19-induced lockdown. The control on construction-related activities could also have contributed to the decrement observed in PM_{2.5} and PM₁₀ concentrations. The decrease in ambient SO₂ concentration during the control period was reported to be proportional to the decreased emission from industrial activities (Dantas et al., 2020; Mahato et al., 2020). Although there was a decrease in air pollution in many countries of the world during the lockdown, restricted anthropogenic activities were not sufficient alone to explain the reduction in the level of pollutants in the air. A study from China reported that due to the partial effect of unfavorable meteorological conditions, the reduction ratios of PM_{2.5} concentrations, as a result of lockdown, were smaller than the reduction ratios of precursor emissions (Wang et al., 2020), indicating the influence of weather on ambient pollutant concentrations. Even though the major air pollutants, such as PM_{2.5}, PM₁₀, CO, NO₂, SO₂ and ammonia (NH₃), saw a large reduction in their concentrations, the concentration of ozone O₃ increased during the lockdown period in many parts of the world as observed in the present study (Collivignarelli et al., 2020; Dantas et al., 2020; Mahato et al., 2020). The slight increase in O₃ can be attributed to the increased photochemical activity due to the decrease in particulate matter concentration (Dang and Liao, 2019; Li et al., 2018). Reduced PM in air results in increased photochemical activities and thus higher O₃ production by giving way for more sunlight to pass through the atmosphere (Dang and Liao, 2019; Li et al., 2018). This may also be due to the favorable conditions for ozone formation,

such as high temperatures and solar radiation indices (Dantas et al., 2020; Escudero et al., 2019). The decrease in NO_x concentration in the atmosphere (Monks et al., 2015) and reduced utilization of O₃ by NO was also probably the reasons behind the increase in O₃ concentrations during the control period. This also shows that meteorological conditions are an important parameter. The simultaneous control of PM_{2.5} and O₃ is quite difficult, and it requires measures such as proper adjustment of industrial structure and energy structure (Li et al., 2020).

The Pearson correlation is significant for a pair when $p < 0.05$. The PM₁₀-PM_{2.5} pair is positively correlated before (0.880) and after (0.746) the lockdown, which suggests a common source for most of these pollutants. The coefficients for the pairs PM₁₀-NO₂ and PM_{2.5}-NO₂ are also significant. Motor vehicles being a common source of particulates and NO₂, could have contributed to this correlation (Kurtenbach et al., 2012). The higher correlation between reductions in PM_{2.5} and NO₂, compared to the correlations of their concentrations in ambient air before and after lockdown, perhaps indicates that their reductions to a great extent can be attributed to the removal of diesel vehicles from roads due to lockdown (Dantas et al., 2020). An interesting observation was the positive correlation of PM₁₀ and PM_{2.5} with O₃ after the lockdown period. This probably indicates that a significant source of PM after lockdown is photochemical reactions (Mangia et al., 2015) that also result in the formation of O₃ (North Earth Observatory, 2003). With most of the anthropogenic sources of primary particulate matter cut down, a good proportion of the available particulate matter might be the secondary particulate matter formed due to chemical reactions between various existing pollutants (Huang et al., 2021). Before the lockdown period, PM₁₀/O₃ and PM_{2.5}/O₃ were either uncorrelated or negatively correlated. There is no significant correlation in the case of NO₂/SO₂, SO₂/O₃ and NO₂/O₃ both before and after the lockdown period, indicating that these pollutant pairs are from different sources.

4.2. Perceived air quality

Most people perceived the air as moderately polluted before lockdown (Fig. 13 a). From the plots (Fig. 13b) obtained for the perception of air quality after lockdown, it is clear that most people perceived air quality as satisfactory or good. Therefore, it can be interpreted that the lockdown has created a positive feeling among people regarding the air quality in the country. The analysis of the air quality before and after lockdown obtained from the various air quality monitoring stations clearly showed an improvement in air quality after lockdown, attributed mainly to the reduction in traffic and industrial activities. However, the lockdown would not have had much influence on other contributing factors like the burning of agricultural wastes, the burning/decomposition of solid wastes, etc. As we all know, in many major cities in the Indo-Gangetic Plain in India, especially Delhi, stubble burning has a great impact on air pollution (Nair et al., 2020). However, in the winter beginning in October, the impact of stubble burning on air pollution has become more pronounced (Sahu et al., 2015). Burning of the solid waste generated locally could have been a major source of air pollution during the lockdown period, though we were not able to verify it using the monitoring data. However, one of the major perceived sources of air pollution during the lockdown as revealed by our perception study was solid waste burning. The results of Google's trend analysis show the lack of influence of the media on the public's perception of air quality. Similar inferences were made by Searle et al., (2020) and Szmuda et al., (2020).

There are various factors other than the actual levels of pollution that shape the perception of pollution. The perception of air quality was shown to be correlated with factors such as gender, education, age, health status, residential location, etc. (Guo et al.,

2016; Oltra and Sala, 2018). The gender of the subjects considered was found to be associated with perception by Elliott et al. (1999). They found that most of the female respondents felt the poor air quality will lead to severe health effects compared to the male respondents. Howel et al. (2003) reported that aged responders had a more negative perception of pollution than younger responders, attributable, possibly, to their bad environmental experience during their younger ages. In another study, subjects older than 40 years, living in an urban area, having a college-level education and poor child health conditions perceived the air quality around the area as worse (Guo et al., 2016). Awareness on air pollution and the associated health effects increases with increase in education level (Liao et al., 2015; Odonkor and Mahami, 2020). The respondents with respiratory indications (nocturnal shortness of breath, phlegm, rhinitis, etc.) reported greater levels of annoyance for degraded air quality (Jacquemin et al., 2007). Factors such as health status, smoking, and exposure time reportedly also have a significant impact on the perception of air quality (Pantavou et al., 2018). But in the present study influence of such factors were not determined which is a limitation of the study. However, proximity to industries and heavy traffic regions were seen to cause negative perceptions on the air quality and health risks associated with it among our respondents as reported by some studies (Brody et al., 2004; Howel et al., 2003; Kohlhuber et al., 2006). Nikolopoulou et al., (2011) observed a good correlation between perceived air quality and PM concentrations in the study area. As the concentration of particulate matter increases, the number of votes for “poor air quality” increased and the number of votes for “good air quality” decreased.

When it comes to human health, a correct understanding of pollution has significant advantages. The OR obtained in Case 2 was 5.2 (95%, CI: 2.69, 10.01), indicating that those who have perceived significant improvement in air quality have perceived significant health improvement. Similarly, other studies have shown that perceived air pollution and perceived health risks play an important role in the manifestation of health symptoms and contribute to illness (Brosschot et al., 2006; Lloyd et al., 2005). In many cases, these health symptoms act as protective mechanisms against the severe consequences of pollution (Engen, 1991). Often, the sources of pollutants may be identified based on olfactory sensations (pleasant or unpleasant). If the source is deemed unpleasant, it is more likely to harm human health (Sucker et al., 2008). In addition to the olfactory system, the trigeminal nerve sensory system activated by vapor substances and particles also plays a prominent role in this perception. The sensation generated by trigeminal chemoreception includes pungency and irritation, where the reflex action prevents the inhalation of hazardous substances (Silver, 1991). Perception studies on air quality have a significant role in creating awareness among people on the importance of having clean air (Evans et al., 1988; Liu et al., 2017). It turns out that a considerable number of people are willing to take steps to reduce air pollution because they think the air quality is bad (Li et al., 2016; Semenza et al., 2008). Perception studies have helped to provide suggestions to the government for improving air quality (Lan et al., 2016; Li et al., 2016). Wang et al. (2015) observed that 90% of respondents from Shanghai, China agreed that improving air quality is the responsibility of the government as well as the citizens. The responses obtained in our study show that 78.7% think that it is the responsibility of citizens to control air pollution. Only 11.5% felt it is the government's job. 9.8% were not sure about who should be responsible.

4.3. Relationship between PAQ and AAQ

The results from the paired *t*-test showed that there was a significant difference ($p < 0.05$) in air quality perception before and

after lockdown (Table 3). Similarly, there is a significant difference ($p < 0.05$) in actual air quality before and after lockdown. However, there is no significant difference ($p > 0.05$) between the pairs ‘air quality perception before lockdown - actual air quality before lockdown’ and ‘air quality perception after lockdown - actual air quality after lockdown’. This shows that there is a clear association between air quality perception and actual air quality. On conducting the test of significance between air quality perception and the converted rating scale of actual air quality, interesting results were found. There was no significant difference ($p > 0.05$) between air quality perception and PM₁₀ level, but there was a significant difference between the perception and levels of SO₂, NO₂ and O₃ ($P = 0.00$). This shows that among various pollutants, PM influenced perception most, possibly because of its contribution to visibility. Several studies have shown a clear relationship between PM₁₀ concentration and visibility, with an increase in PM₁₀ levels resulting in lower visibility (Huang et al., 2016; Zhao et al., 2013). In earlier days, before the invention of air quality monitoring instruments, visibility was the parameter that was used to assess air quality. The deterioration of visibility is caused by the scattering and absorption of visible light by suspended particles and gaseous pollutants in the atmosphere (Hyslop, 2009; Lee et al., 2015; Majewski et al., 2015). In the urban environment, the deterioration of visibility is closely related to pollutants emitted by man-made sources, such as automobile exhaust, fuel combustion, industrial emissions, etc. (Deng et al., 2008; Majewski et al., 2015; Tsai et al., 2007). It was also observed that this visibility impairment is mainly due to airborne particulate matter (Malm and Day, 2001; Tsai et al., 2003).

The OR obtained in case I is 17 (95%, CI: 6.42, 47.04), which indicates that the perceived improvement in air quality is highly dependent on the actual improvement in the air quality. Higher odds ratios indicate higher dependence between PAQ and AAQ.

4.4. Qualitative interpretation of the suggestions

The words were decoded from the suggestions based on the frequency of appearance. The suggestions given by the respondents were to lift the lockdown scientifically, to implement strict regulations concerning traffic, industries, vehicular emissions and trash burning on road margins, living in harmony with nature, strengthening public transportation and adoption of carpooling systems, promotion of E-vehicles and bio-fuels, plantation of trees, installation of air quality monitors across the country and creating awareness among the public about the improvement in air quality levels and maintenance of the same.

5. Conclusion

From this study, it is evident that there was a significant improvement in the actual and perceived air quality in India after the COVID-19-induced lockdown. Approximately 60% of the respondents perceived improvement in air quality, and there was approximately 40% improvement in the monitored air quality across the country. The respondents perceived improvement in air quality without the influence of media. The reduction in air pollution was investigated concerning three different zones. Major traffic zones across the country have experienced significant improvement in the NO₂ level due to the decrease in vehicular load. Similarly, a significant reduction in SO₂ levels was observed in industrial belts and coal mines. The correlation matrix developed gave a clear association between the pollutants and the possible sources. During the lockdown period, an increased photochemical reaction was observed, which led to an elevation in the concentration of ozone at many locations. Along with

improvements in air quality, significant improvements in visibility, indoor air quality and health were perceived by the respondents. Household emissions were perceived to be major source of pollution during the lockdown period. The perception of improvement in air quality was influenced mainly by the reduction in particulate matter. The odds ratio showed a very strong dependence of perception on actual air quality and strong association between air quality improvement and health improvement. Suggestions by the public for maintaining air quality even after lifting the COVID-19 lockdown are also given in this study.

CRediT authorship contribution statement

Abinaya Sekar: Conceptualization, Methodology, Writing – original draft, Visualization, Formal analysis. **R.S. Jasna:** Writing – original draft, Formal analysis. **B.V. Binoy:** Visualization. **Prem Mohan:** Formal analysis, Investigation. **George Kuttiparichel Varghese:** Conceptualization, Methodology, Validation, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.gr.2022.04.023>.

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